

AD-A256 817

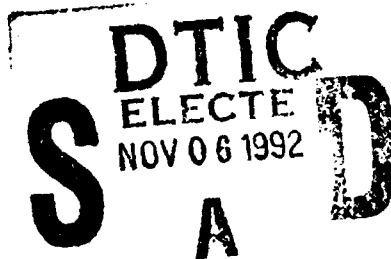


2

A RAND NOTE

User's Guide for the Longitudinal
Scalogram Analysis Program

Ron D. Hays



This document has been approved
for public release and sale; its
distribution is unlimited.

92-29007



RAND

92 11 005

The research described in this report was supported by a grant from the Conrad N. Hilton Foundation and by RAND using its own research funds.

The RAND Publication Series: The Report is the principal publication documenting and transmitting RAND's major research findings and final research results. The RAND Note reports other outputs of sponsored research for general distribution. Publications of RAND do not necessarily reflect the opinions or policies of the sponsors of RAND research.

A RAND NOTE

N-3260-1-CHF/RC

User's Guide for the Longitudinal Scalogram Analysis Program

Ron D. Hays

DTIC QUALITY INSPECTED 4

Supported by the
Conrad N. Hilton Foundation

Accession For	
NTIS CRA&I	<input checked="" type="checkbox"/>
DTIC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution /	
Availability Codes	
Dist	Avail and/or Special
A-1	

RAND

PREFACE

This Note is the user's manual for the Longitudinal Scalogram Analysis (LSA) program. LSA is an extension of cross-sectional scalogram analysis to longitudinal data. The LSA program has been used on Project ALERT to model stages of drug use involvement in adolescents. This revision of the original Note adds new information about the computation of standard errors and provides an example illustrating different longitudinal scalogram results for the same prevalence rates.

The development of the LSA program was made possible by a grant from the Conrad N. Hilton Foundation and support from RAND. The opinions expressed are those of the author and do not necessarily reflect the views of the sponsor or RAND.

The program and this manual benefited from insightful comments by RAND colleagues John Uebersax and Phyllis Ellickson, and from suggestions made by Paul Baerman and two anonymous reviewers (recruited by Duke University Press). Appreciation is also expressed to Pat Bedrosian for helpful editorial suggestions and Kim Wong for secretarial support.

CONTENTS

PREFACE	iii
TABLES	vii
Section	
I. INTRODUCTION	1
II. UNDERSTANDING LONGITUDINAL SCALOGRAM ANALYSIS	2
III. USING THE LONGITUDINAL SCALOGRAM ANALYSIS PROGRAM	7
IV. APPLYING LONGITUDINAL SCALOGRAM ANALYSIS	17
V. AVAILABILITY	19
VI. A SUMMARY OF ALTERNATIVE ANALYTIC METHODS	19
BIBLIOGRAPHY	21

TABLES

1. Example of Pattern of Responses to Three Items Fitting Perfectly a Cross-Sectional Guttman Scale	2
2. Example of Pattern of Responses to Three Items Fitting Perfectly a Three-Wave Longitudinal Guttman Scale	4
3. Comparing Example Pattern to Patterns Consistent with a Longitudinal Guttman Scale: Three Items, Three Waves, and a Total Score of 5	5
4. Example RAW File	7
5. Example INPUT File	8
6. Example OUTPUT File	14
7. Dialog of PRELSA.EXE	16
8. Response Patterns for 791 Respondents from Kandel and Faust (1975)	18
9. Substantive Example Illustrating an Absence of Longitudinal Transitions ..	19
10. Substantive Example Illustrating How Same Prevalence Rates Can Lead to Different Longitudinal Scalogram Results	18

I. INTRODUCTION

This Note is the user's manual for the Longitudinal Scalogram Analysis (LSA) program. LSA is an extension of cross-sectional scalogram analysis to longitudinal data. An application of this program using Project ALERT data is provided in Ellickson, Hays, and Bell (forthcoming).

II. UNDERSTANDING LONGITUDINAL SCALOGRAM ANALYSIS

Unitary growth characterizes a variety of different developmental processes including intellectual development (e.g., Bayley, 1955), drug use involvement (e.g., Kandel, 1975), moral development (Walker, deVries, and Bichard, 1984), and functional health (Stewart, Ware, and Brook, 1981). The common feature of these different domains is a deterministic, cumulative sequence of development. Cross-sectional Guttman scale analysis has been employed as the "bread and butter" method for evaluating these processes (Guttman, 1944). The Guttman scale model is straightforward and easy to interpret. If observed data fit a Guttman scale, then all persons with the same scale score (i.e., sum of endorsed items in the scale) have identical responses to each item in the scale. In general, the number of possible response patterns is two raised to a power equal to the number of items, but the number of response patterns consistent with a Guttman scale equals the number of items plus one (Dotson and Summers, 1970; Schwartz, 1986).

Table 1 presents the item response patterns expected for three items forming a Guttman scale of measurement: magnitude, equal interval, and absolute zero. Eight response patterns are possible, but only the four shown in Table 1 are consistent with a Guttman scale. Knowing that a scale has an absolute zero point allows for the inference that it has equal intervals and that it has the property of magnitude.

Similarly, knowing that a scale has equal intervals leads to the prediction that it possesses the property of magnitude. In contrast, knowing that a scale has magnitude does not allow one to infer whether or not it has equal intervals or an absolute zero point.

Table 1

EXAMPLE OF PATTERN OF RESPONSES TO THREE ITEMS FITTING PERFECTLY A CROSS-SECTIONAL GUTTMAN SCALE

Type of Scale	Magnitude?	Equal Interval?	Absolute Zero?	Total Score
Nominal	No	No	No	0
Ordinal	Yes	No	No	1
Interval	Yes	Yes	No	2
Ratio	Yes	Yes	Yes	3

The scalability of responses is determined by comparing observed patterns of data with the patterns predicted for a Guttman scale, examining the degree to which observed response patterns deviate from expected response patterns. The coefficient of reproducibility (CR) for Guttman scales is defined as the proportion of error (i.e., proportion of differences between observed and expected responses) subtracted from unity. A CR value of 0.90 or higher is considered acceptable. In addition, an index of reproducibility is typically computed by determining how well item modes reproduce the observed response patterns. Errors are counted as differences between each observed item response for an individual and the modal response for that item across all respondents using the Goodenough (1944) procedure. This index, the minimum marginal reproductibility (MR), is used to calculate the coefficient of scalability (CS) defined as $(CR - MR)/(1 - MR)$. A CS of 0.60 has been recommended as a minimum standard for acceptability (Menzel, 1953).

Traditional Guttman scalogram analysis is limited to evaluating item order cross-sectionally. Longitudinal scalogram analysis (LSA) is an extension of traditional scalogram analysis that incorporates the element of time (Hays and Ellickson, 1990). Table 2 presents response patterns for three items measured at three time points. As illustrated in Table 2, only one pattern of responses is longitudinally consistent with a total score of 0, 1, 8, or 9 "yes" answers. However, there are two different response patterns consistent with two or seven affirmative answers and three different response patterns consistent with a total of three, four, five, or six affirmative answers. For example, a total score of 2 may be obtained for a scale having the property of magnitude at time 2 and time 3 or by a scale having magnitude and equal interval properties at time 3 (assuming that scales can change over time). In general, the number of possible response patterns is two raised to a power equal to the product of the number of items and waves. The number of patterns consistent with a longitudinal Guttman scale is:

$$\frac{(\text{items} + \text{waves})!}{\text{items! waves!}}$$

Because of the multiple response patterns consistent with a longitudinal Guttman scale, calculating reproducibility and scalability is not as straightforward for longitudinal as it is for cross-sectional data.

Table 2

EXAMPLE OF PATTERN OF RESPONSES TO THREE ITEMS
FITTING PERFECTLY A THREE-WAVE LONGITUDINAL
GUTTMAN SCALE

A1	B1	C1	A2	B2	C2	A3	B3	C3	Total Score
No	No	No	No	No	No	No	No	No	0
No	No	No	No	No	No	Yes	No	No	1
No	No	No	Yes	No	No	Yes	No	No	2
No	No	No	No	No	No	Yes	Yes	No	2
No	No	No	Yes	No	No	Yes	Yes	No	3
No	No	No	No	No	No	Yes	Yes	Yes	3
Yes	No	No	Yes	No	No	Yes	No	No	3
No	No	No	Yes	Yes	No	Yes	Yes	No	4
No	No	No	Yes	No	No	Yes	Yes	Yes	4
Yes	No	No	Yes	No	No	Yes	Yes	No	4
No	No	No	Yes	Yes	No	Yes	Yes	Yes	5
Yes	No	No	Yes	Yes	No	Yes	Yes	No	5
Yes	No	No	Yes	No	No	Yes	Yes	Yes	5
No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	6
Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	6
Yes	No	No	Yes	Yes	No	Yes	Yes	Yes	6
Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	7
Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes	7
Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	8
Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	9

NOTE: A = magnitude, B = equal interval, C = absolute zero.

With longitudinal data, the expected pattern against which observed scores are compared cannot be determined solely on the basis of the total score across items. However, identification of all longitudinal patterns that are consistent with the Guttman model and yield the total score observed for each individual can be used to select the pattern (i.e., "expected pattern") that is minimally different from observed scores. Table 3 provides an example of selecting the expected pattern for a total score of 5 and observed score pattern of 001 111 100 for three items measured at three time points. The minimum difference

between the observed pattern and the three patterns consistent with a longitudinal Guttman scale and yielding the same total score is 4. This difference is observed for two of the three patterns; thus, either of these patterns can serve as the expected pattern (i.e., they are equivalent for the purpose of computing scalogram errors).¹

Once the expected pattern has been determined, longitudinal coefficients of reproducibility (LCR) and scalability (LCS) can be computed as in cross-sectional Guttman scalogram analysis. Subtracting the proportion of errors from unity yields LCR. LCS is defined as the difference between LCR and the reproducibility of items from their modes (LMR), divided by LMR subtracted from unity: $LCS = (LCR - LMR)/(1 - LMR)$.²

Previous research using Guttman scalogram analysis has not reported estimates of sampling error for the coefficient of reproducibility. Green (1956) noted that the standard error of the CR can be approximated by $[CR(1 - CR)/N K]^{1/2}$, an adaptation of the formula for the standard error of a proportion (N = number of respondents, K = number of items).

Table 3

COMPARING EXAMPLE PATTERN TO PATTERNS CONSISTENT
WITH A LONGITUDINAL GUTTMAN SCALE: THREE ITEMS,
THREE WAVES, AND A TOTAL SCORE OF 5

Time			Difference Between Patterns	Type of Response Pattern
1 Item 1 2 3	2 Item 1 2 3	3 Item 1 2 3		
0 0 1	1 1 1	1 0 0	—	Example pattern
0 0 0	1 1 0	1 1 1	4	Longitudinally consistent pattern #1
1 0 0	1 1 0	1 1 0	4	Longitudinally consistent pattern #2
1 0 0	1 0 0	1 1 1	6	Longitudinally consistent pattern #3

NOTE: 0 = not passed, 1 = passed.

¹As an alternative to narrowing down the potential expected patterns based on the total score, one can compare each score with all longitudinally consistent patterns to identify the pattern that is least different. This alternative procedure yields scaling coefficients (reproducibility and scalability) that are as large or larger than those obtained from the standard method. However, we observed a tenfold increase in execution time using this alternative procedure on Project ALERT data (Ellickson, Hays, and Bell, forthcoming).

²The LSA error-counting procedure is directly analogous to cross-sectional Guttman scalogram analysis and weights equally different scaling inconsistencies. An argument could be made for differential weighting of errors (e.g., endorsing an item out of sequence at wave 1 might be considered worse than endorsing the same item at a later wave).

Although this formula provides a reasonable approximation for the original Cornell method of calculating reproducibility, it requires modification for use with the "double-counting" Goodenough (1944) scoring method. The following formula is more appropriate for estimating the standard error of reproducibility for Goodenough scoring: $[(1 + CR) (1 - CR)/N K]^{1/2}$. The Longitudinal Scalogram Analysis program computes approximate standard errors using this latter formula and it calculates the actual standard errors, using the fact that the coefficient for a sample is the average of coefficients for members of the sample.

III. USING THE LONGITUDINAL SCALOGRAM ANALYSIS PROGRAM

The Longitudinal Scalogram Analysis program, LSA.EXE, is a compiled BASIC program that runs under the DOS 2.0 or later on IBM PC or compatible microcomputers. LSA.EXE outputs the proportion of the sample passing each item, the number of respondents in the analysis, a frequency distribution of the number of scaling errors, and the longitudinal coefficients of reproducibility and scalability, LCR and LCS. Cross-sectional coefficients of reproducibility and scalability are provided for each wave of data. In addition, the universe of response patterns perfectly consistent with a longitudinal Guttman scale for the given number of items and waves is printed, sorted by the number of endorsed items. LSA.EXE is limited to four waves (time points) of data and nine items per wave (if four waves of data are analyzed). A sample size of up to 4,500 cases can be analyzed (the frequency of all response patterns is available only for sample sizes of 1,250 or less).

To run the LSA.EXE program, the user needs a raw data (ASCII) input file. Table 4 provides an example raw data file, RAW (the default file name), consisting of 11 respondents, two waves of data, and three items at each wave. This raw data file has been constructed so that more recent data-collection waves precede later waves. In the example, wave 2 data appear first, followed by wave 1 data. However, the user can arrange the data in any order desired. Items in the analysis are coded as either "0" (item not endorsed) or "1" (item endorsed). If any of the input items has a value other than "0" or "1," LSA.EXE excludes the case from the analysis.

Table 4

EXAMPLE RAW FILE

```
1100000
1000000
1000000
1100100
1110110
1111111
1101101
1011011
1011011
0000000
0111101
```

Program input specifications are supplied in a second file, as shown in the example input specification file in Table 5. This input specification file, INPUT (the default file name), consists of eight keywords: TITLE, NCASES, WAVES, SELECT, HOWREAD, ITEMS, LCSMAX, and FREQUENCY. The TITLE keyword is followed by a one line descriptive title. Following the NCASES keyword, the user specifies the number of respondents in the RAW input file. The number of data waves are indicated after the WAVES keyword. The SELECT keyword is optional and is used only when one wants to select a subset of the RAW cases for analysis. If the SELECT option is used, the line following the SELECT keyword is used to designate the value of the selection variable.

The HOWREAD keyword appears next. Following the HOWREAD keyword is the full input specification (FORTRAN-type input format), including the SELECT variable (if applicable) and analysis variables. If the SELECT keyword is not used (and therefore the whole sample is used), then the input specification following the HOWREAD keywords includes only items in the analysis.

Table 5

EXAMPLE INPUT FILE

TITLE
Sample Data File of 11 Cases
NCASES
11
WAVES
2
SELECT
1
HOWREAD
(711)
ITEMS
6
'LOW2' 1
'MED2' 2
'HIGH2' 3
'LOW1' 4
'MED1' 5
'HIGH1' 6
LCSMAX
Yes
FREQUENCY
Yes
END

The ITEMS keyword is listed next, followed by the number of items in the analysis (number of items at each wave times the number of waves). The item names are listed on consecutive lines corresponding to the HOWREAD input specification. On each line following the item name is a rank order number. The numbers following the item names collectively inform LSA.EXE about the hypothesized structure in the data. LSA.EXE uses these numbers to order the items for analysis. The number adjacent to the first item name indicates where the first item in the sequence at the most recent wave is located among all items in the analysis. In the example input file in Table 5, the number "1" is shown next to the LOW2 item, "2" next to the MED2 item, and so forth. The "1" tells LSA.EXE that the first item in the sequence (at the most recent wave) is ordered first in the list of items. Thus, the first item for this example is LOW2. Similarly, the "2" informs the program that the second item in the list of items is ordered second in the list of items; therefore, the second item in the sequence is MED2. The third number in the column of numbers designates the location of the third item at the most recent wave, and so on. Once the items for the most recent wave are completed, the corresponding items at earlier waves are designated. If MED2 was hypothesized as the first item in the sequence at the most recent wave and LOW2 as the second item, then this section of INPUT file would be changed as follows:

```
ITEMS
6
'LOW2' 2
'MED2' 1
'HIGH2' 3
'LOW1' 5
'MED1' 4
'HIGH1' 6
```

The LCSMAX keyword indicates whether or not the user wants the program to compute longitudinal coefficients of scalability by comparing each score with all longitudinally consistent patterns to identify the pattern that is least different. As noted above, this alternative procedure is more computationally intensive than the standard method. If these additional coefficients are desired, the LCSMAX keyword needs to be followed by a line with the word "Yes" (upper or lowercase is acceptable). Otherwise this line should contain the word "No." Similarly, the FREQUENCY keyword is used if a frequency distribution of responses is desired.

After RAW and INPUT have been created, execution is initiated by typing "GO" and touching the Enter (Return) key. The GO command activates a batch file that calls three subprograms. The first, LS.EXE, reads the input specification file (e.g., INPUT) and the input raw data file (e.g., RAW) and writes out a new file, OUTPUT, that integrates the two input files. Next, the main subprogram, LLL.EXE, executes and writes out the primary scalogram output to one file and the universe of perfect longitudinal patterns for the given number of items and waves to a separate file. Finally, the last subprogram, LL.EXE, computes the frequencies of response patterns, if frequencies were requested using the FREQUENCY keyword. The batch file integrates the output of the subprograms together into one file, OUTPUT. This output file can be printed using the DOS "print" command.

The OUTPUT file produced by the example RAW and INPUT files is given in Table 6. Note that nine of the 11 respondents were selected for the analysis on the basis of the selection criteria.

Included on the distribution diskette is a program, PRELSA.EXE, that can be used to create the input specification file for LSA.EXE. PRELSA.EXE was written as a user-friendly device for those who prefer answering structured questions rather than creating the input specification file directly.

The user runs PRELSA.EXE by typing "PRELSA" and touching the Enter (Return) key. PRELSA.EXE then asks a series of questions and uses the responses to create an input specification file, INPUT. (Warning: If a file is saved on the default drive with the name "INPUT," it will be overwritten when PRELSA is executed.) PRELSA.EXE seeks eight pieces of information: the title for the analysis, the number of cases in the raw data file, the number of waves of data, whether or not a subsample analysis will be done, the number of items in the analysis, the selection variable and its column location (if applicable), item names, column locations and rank ordering of items, whether or not errors are to be calculated using the intensive computation method, and whether or not the frequency of response patterns will be printed. The text of these inquiries is provided in Table 7.

Table 6

EXAMPLE OUTPUT FILE

LONGITUDINAL SCALOGRAM ANALYSIS (LSA) PROGRAM (VERSION 2.1)
BY R. D. HAYS
RAND

Sample Data File of 11 Cases

ITEM	PROPORTION PASSING	
Wave = 2		
1	0.56	LOW2
2	0.44	MED2
3	0.44	HIGH2
Wave = 1		
1	0.44	LOW1
2	0.44	MED1
3	0.44	HIGH1

NUMBER OF SUBJECTS = 9

LONGITUDINAL SCALOGRAM ANALYSIS

95% Confidence Interval

COEFFICIENT OF REPRODUCIBILITY (MAX)	=	0.8889	
COEFFICIENT OF SCALABILITY (MAX)	=	0.7500	
COEFFICIENT OF REPRODUCIBILITY (LCR)	=	0.8148	(0.6188 -- 1.10108)
ESTIMATED STANDARD ERROR OF LCR	=	0.0789	
ACTUAL STANDARD ERROR OF LCR	=	0.0980	
MINIMUM MARGINAL REPRODUCIBILITY	=	0.5556	
PERCENT IMPROVEMENT	=	0.2593	
COEFFICIENT OF SCALABILITY	=	0.5833	
PROPORTION PERFECT GUTTMAN PATTERNS	=	0.6667	

CROSS-SECTIONAL SCALOGRAM ANALYSIS

COEFFICIENT OF REPRODUCIBILITY WAVE 2	=	0.7778	(0.5556 -- 1.0000)
ESTIMATED STANDARD ERROR OF LR	=	0.1210	
ACTUAL STANDARD ERROR OF LR	=	0.1111	
MINIMUM MARGINAL REPRODUCIBILITY	=	0.5556	
PERCENT IMPROVEMENT	=	0.2222	
COEFFICIENT OF SCALABILITY	=	0.5000	
COEFFICIENT OF REPRODUCIBILITY WAVE 1	=	0.7778	(0.5556 -- 1.0000)
ESTIMATED STANDARD ERROR OF LR	=	0.1210	
ACTUAL STANDARD ERROR OF LR	=	0.1111	
MINIMUM MARGINAL REPRODUCIBILITY	=	0.5556	
PERCENT IMPROVEMENT	=	0.2222	
COEFFICIENT OF SCALABILITY	=	0.5000	

Table 6—continued

FREQUENCY OF SCALING ERRORS

0 ***** (6)

2 * (1)

4 ** (2)

FREQUENCIES FOR ALL RESPONSE PATTERNS:

Pattern		Frequency
W2	W1	
000	000	: (2)
000	000	: (2)
000	000	: (2)
011	011	: (2)
100	000	: (1)
100	100	: (1)
101	101	: (1)
110	110	: (1)
111	111	: (1)

PERFECT LONGITUDINAL PATTERNS FOR GIVEN NUMBER OF ITEMS AND WAVES

N PASSED	SEQUENCE	PATTERN
0	1	000 000
1	2	100 000
2	3	100 100
2	4	100 100
2	5	110 000
3	6	110 100
3	7	110 100
3	8	111 000
4	9	110 110
4	10	110 110
4	11	110 110
4	12	111 100
4	13	111 100
5	14	111 110
5	15	111 110
5	16	111 110
6	17	111 111
6	18	111 111
6	19	111 111
6	20	111 111

Table 7

DIALOG OF PRELSA.EXE

-
1. WHAT IS THE TITLE FOR THIS ANALYSIS?
(TYPE 80 ALPHANUMERIC COLUMNS OR LESS)
 2. HOW MANY CASES ARE THERE IN THE RAW DATA FILE?
 3. HOW MANY WAVES OF DATA ARE THERE?
 4. IS THIS A SUBSAMPLE ANALYSIS?
THAT IS, ARE YOU SUBSETTING THE SAMPLE?
1 = YES
2 = NO
 - 4B. WHAT VALUE ARE YOU SELECTING ON?
(VALUE OF THE SELECTION VARIABLE USED TO SELECT THE SUBSAMPLE)
 5. HOW MANY ITEMS ARE IN THE ANALYSIS?
(NUMBER OF ITEMS AT EACH WAVE X NUMBER OF WAVES)
 - 5B. SELECTION VARIABLE:

NAME	BEGINS IN COLUMN	ENDS IN COLUMN
?	?	?

6. PLEASE TYPE THE ITEM NAME, COLUMN LOCATION (IN RAW DATA FILE),
AND RANK ORDER OF EACH ITEM IN THE ANALYSIS.

RANK ORDER 1 IS THE ITEM HYPOTHESIZED TO BE MOST PREVALENT AT THE MOST
RECENT WAVE. RANK ORDER 2 IS THE ITEM HYPOTHESIZED TO BE SECOND MOST
PREVALENT AT THE MOST RECENT WAVE.

ITEM NAME	COLUMN NUMBER	RANK ORDER
ITEM: ?	?	?

7. DO YOU WANT TO CALCULATE ERRORS USING THE INTENSIVE COMPUTATION
METHOD?
1 = YES
2 = NO
 8. DO YOU WANT A PRINTOUT OF THE FREQUENCY OF RESPONSE PATTERNS?
1 = YES
2 = NO
-

IV. APPLYING LONGITUDINAL SCALOGRAM ANALYSIS

Kandel and Faust (1975) provided cross-tabulations of drug use stages at the end of the senior year by use reported during a subsequent five to nine month time interval for 872 public secondary school students. Applying the LSA methodology to these data allows an evaluation of the hypothesis that cumulative drug use reported at the end of high school continues as current use during a time span immediately following high school.

About 95 percent of the sample reported drug use that was cross-sectionally consistent (i.e., had no errors) at both time points with a seven-level Guttman scale: nonuse, use of legal drugs, cannabis, pills, psychedelics, cocaine, and heroin. The LSA analysis was restricted to these respondents ($n = 791$), because complete information about response patterns was not discernible in the original article for the rest of the sample. The data for this subsample (see Table 8) support the hypothesized longitudinal Guttman scale, although there were some relapses (i.e., items not passed at time 2 that were passed at time 1) and these are reflected in the less-than-perfect longitudinal scalogram coefficients ($LCR = 0.97$, $LCS = 0.72$). Cross-sectional Guttman scale analysis of the two waves of data is insensitive to these relapses (i.e., $CS = 1.0$ at both time points), because it ignores the dimension of time.

Examination of the longitudinal scaling errors reveals that the majority involve two types: persons who reported (1) having tried legal drugs but abstained after high school, and persons who reported (2) having tried legal drugs and cannabis but abstained from cannabis after high school.

In the special case where no longitudinal transitions occur (i.e., the cross-sectional hierarchy among items contains all the information, as in the example shown in Table 9), the LCS index is not simply the average of the cross-sectional scalability coefficients. In general, the LCS value will exceed the average of the CS values because longitudinal data offer greater flexibility in identifying target response patterns that minimize scalability errors. For example, $LCS = 0.62$ for the data shown in Table 9 while $CS = 0.50$ for both waves of data.

Table 10 provides a clear example of why the same prevalence rates can result in different longitudinal scaling results. Hypothetical data that would lead to opposite conclusions about a hypothesized sequence of drug use (from alcohol use to marijuana use to hard drug use) are shown. Note that in both panels of Table 10 the prevalence of alcohol use

Table 8

RESPONSE PATTERNS FOR 791 RESPONDENTS
FROM KANDEL AND FAUST (1975)

Time 1						Time 2						Frequency
Item						Item						
1	2	3	4	5	6	1	2	3	4	5	6	
0	0	0	0	0	0	0	0	0	0	0	0	36
0	0	0	0	0	0	1	0	0	0	0	0	22
0	0	0	0	0	0	1	1	0	0	0	0	3
0	0	0	0	0	0	1	1	1	1	1	1	1
1	0	0	0	0	0	0	0	0	0	0	0	33*
1	0	0	0	0	0	1	0	0	0	0	0	345
1	0	0	0	0	0	1	1	0	0	0	0	76
1	0	0	0	0	0	1	1	1	0	0	0	5
1	1	0	0	0	0	1	0	0	0	0	0	35*
1	1	0	0	0	0	1	1	0	0	0	0	106
1	1	0	0	0	0	1	1	1	0	0	0	13
1	1	0	0	0	0	1	1	1	1	0	0	5
1	1	0	0	0	0	1	1	1	1	1	0	2
1	1	1	0	0	0	1	0	0	0	0	0	8*
1	1	1	0	0	0	1	1	0	0	0	0	12*
1	1	1	0	0	0	1	1	1	0	0	0	20
1	1	1	0	0	0	1	1	1	1	0	0	5
1	1	1	0	0	0	1	1	1	1	1	0	2
1	1	1	0	0	0	1	1	1	1	1	1	2
1	1	1	1	0	0	1	0	0	0	0	0	8*
1	1	1	1	0	0	1	1	0	0	0	0	13*
1	1	1	1	0	0	1	1	1	0	0	0	10*
1	1	1	1	0	0	1	1	1	1	0	0	8
1	1	1	1	0	0	1	1	1	1	1	0	9
1	1	1	1	1	0	1	1	0	0	0	0	2*
1	1	1	1	1	0	1	1	1	0	0	0	3*
1	1	1	1	1	0	1	1	1	1	0	0	3*
1	1	1	1	1	0	1	0	0	0	0	0	1*
1	1	1	1	1	0	1	1	0	0	0	0	1*
1	1	1	1	1	0	1	1	1	0	0	0	2*

NOTE: Total n = 791. 0 = not passed, 1 = passed. Items are legal drugs, cannabis, pills, psychedelics, cocaine, and heroin. Asterisks denote longitudinal relapses (i.e., items failed at time 2, but passed at time 1).

Table 9

SUBSTANTIVE EXAMPLE ILLUSTRATING AN ABSENCE
OF LONGITUDINAL TRANSITIONS

Time 1			Time 2		
Low	Medium	High	Low	Medium	High
0	0	0	0	0	0
1	0	0	1	0	0
1	1	0	1	1	0
1	1	1	1	1	1
1	0	1	1	0	1
0	1	1	0	1	1

NOTE: Time #1 = entry into kindergarten, Time #2 = beginning of first grade. Three levels of achievement are defined: low, medium, high.

is 0.50 and 0.70 at time 1 and time 2, respectively; the prevalence of marijuana use is 0.20 and 0.30, respectively; and the prevalence of hard drug use is 0.10 and 0.20, respectively. However, LCS = 1.00 for panel A and 0.38 for panel B. Hence the data in panel A provide strong support for the hypothesized sequence of drug use involvement whereas the data in panel B do not.

Table 10

**SUBSTANTIVE EXAMPLE ILLUSTRATING HOW SAME
PREVALENCE RATES CAN LEAD TO DIFFERENT
LONGITUDINAL SCALOGRAM RESULTS**

Time 1			Time 2		
Alc	Mar	Hard	Alc	Mar	Hard
Panel A:					
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	1	0	0
0	0	0	1	0	0
1	0	0	1	0	0
1	0	0	1	0	0
1	0	0	1	1	0
1	1	0	1	1	1
1	1	1	1	1	1
Panel B:					
0	1	0	0	1	0
0	1	0	0	1	0
0	0	0	0	1	0
0	0	1	1	0	1
0	0	0	1	0	1
1	0	0	1	0	0
1	0	0	1	0	0
1	0	0	1	0	0
1	0	0	1	0	0
1	0	0	1	0	0

NOTE: Time #1 = 7th grade, Time #2 = 8th grade. Three levels of drug use are defined: Alc = alcohol, Mar = marijuana, Hard = hard drugs.

V. AVAILABILITY

Copies of LSA.EXE on a floppy diskette may be obtained from Wm. C. Brown Publishers, 2460 Kerper Blvd., Dubuque, IA 52001; phone (319) 588-1451. Employees of RAND may contact the author directly. Questions about the program should be directed to: Ron D. Hays, Ph.D., Social Policy Department, RAND, 1700 Main Street, Santa Monica, CA 90407-2138.

VI. A SUMMARY OF ALTERNATIVE ANALYTIC METHODS

Collins, Cliff, and Dent (1988) were the first to extend cross-sectional Guttman scaling by incorporating the element of time. They developed the Longitudinal Guttman Simplex (LGS) method, which considers four kinds of relations of items and times. Redundant time relations are those in which answers given to a pair of items provide redundant information about two time points (i.e., at one time point both items are failed and at the other time point both are passed). Redundant item relations are those in which the answers to a pair of items match at two time points. Unique relations are those in which responses to only one item in a pair change over time. Contradictory relations provide conflicting information about the relative ordering of both items and times.

Collins, Cliff, and Dent (1988) derived a consistency index, CL, that ranges from negative infinity to positive one (c.f. Cliff, 1979). The weighting scheme used to compute CL was empirically derived based on the ability to distinguish random from nonrandom data and to distinguish among data known to differ in consistency (Collins, Cliff, and Dent, 1988). Unique relations are weighted four times that of redundant and contradictory relations. The total number of weighted consistent relations is computed as the sum of redundant and four times the number of unique relations that are congruent with the a priori item-times order. The proportion of consistent relations is equal to the total number of consistent relations divided by the total number of weighted relations (c.f. Collins, Cliff, and Dent, 1988). Rules of thumb for the CL index have been suggested, but consensus guidelines for interpreting this coefficient have not yet been developed by the research community.

The LGS method, the Longitudinal Scalogram Analysis methodology described in this manual, and traditional Guttman scalogram analysis all ignore measurement error and are deterministic in the sense that they evaluate the extent to which all individuals adhere to the same basic response model. Latent structure analysis, a probabilistic analytic procedure, offers greater flexibility in modeling observed response patterns. For example, Proctor (1970) proposed a latent structure model that explicitly allows for response error. The Proctor model assumes that each scale item has the same error rate. Clogg and Sawyer (1981) presented an even more general model, allowing for specific item error rates and different error rates for different types of respondents. The Proctor model and Clogg and Sawyer procedures are examples of latent class models. Further information about latent

class analysis generally (McCutcheon, 1987) and specific applications to adolescent drug use (Graham, et al., 1991; Sorenson and Brownfield, 1989) are provided elsewhere.

Item-response theory is another form of latent structure analysis in which the distribution of the latent trait is assumed to be continuous (Hambleton and Swaminathan, 1985; Traub and Lam, 1985).

Mixed-Markov modeling is potentially one of the most promising approaches for modeling stage transitions. An excellent introduction to Mixed-Markov models is given by Uebersax, et al. (1990).

BIBLIOGRAPHY

- Bayley, N., "On the Growth of Intelligence," *American Psychologist*, 10, pp. 805-818, 1955.
- Collins, L. M., N. Cliff, and C. W. Dent, "The Longitudinal Guttman Simplex: A New Methodology for Measurement of Dynamic Concepts in Longitudinal Panel Studies," *Applied Psychological Measurement*, 12, pp. 217-230, 1988.
- Cliff, N., "Test Theory Without True Scores?" *Psychometrika*, 44, pp. 373-393, 1979.
- Clogg, C. C., and D. O. Sawyer, "A Comparison of Alternative Models for Analyzing the Scalability of Response Patterns," in S. Leinhardt (ed.), *Sociological Methodology*. Jossey-Bass: San Francisco, 1981.
- Dotson, L. E., and G. F. Summers, "Elaboration of Guttman Scaling Techniques, in G. F. Summers (ed.), *Attitude Measurement*. Rand McNall: Chicago, 1970.
- Ellickson, P. L., R. D. Hays, and R. M. Bell, *Stepping Through the Drug Use Sequence: Longitudinal Scalogram Analysis of Initiation and Heavy Use*, forthcoming, 1991.
- Goodenough, W. H., "A Technique for Scale Analysis," *Educational and Psychological Measurement*, 4, pp. 179-190, 1944.
- Graham, J. W., L. M. Collins, S. E. Wugalter, and N. K. J. Chung, and W. B. Hansen, "Modeling transition of latent stage-sequential processes: A substance use prevention example," *Journal of Consulting and Clinical Psychology*, 59, pp. 48-57, 1991.
- Graham, J. W., C. A. Johnson, W. B. Hansen, B. R. Flay, and M. Gee, "Drug Use Prevention Programs, Gender and Ethnicity: Evaluation of Three Seventh-Grade Project SMART Courts," *Preventive Medicine*, 19, pp. 305-313, 1990.
- Green, B. F., "A Method of Scalogram Analysis Using Summary Statistics," *Psychometrika*, 21, pp. 79-88, 1956.
- Guttman, L., "A Basis for Scaling Qualitative Data," *American Sociological Review*, 9, pp. 139-150, 1944.
- Hambleton, R. K., and H. Swaminathan, *Item Response Theory: Principles and Applications*. Kluwer-Nijhoff Publishing: Boston, 1985.
- Hays, R. D., and P. L. Ellickson, "Longitudinal Scalogram Analysis: A Methodology and Microcomputer Program for Guttman Scale Analysis of Longitudinal Data," *Behavior Research Methods, Instruments & Computers*, 22, pp. 162-166, 1990.
- Kandel, D., "Stages in Adolescent Involvement in Drug Use," *Science*, 190, pp. 912-914, 1975.

- Kandel, D., and R. Faust, "Sequence and Stages in Patterns of Adolescent Drug Use," *Archives of General Psychiatry*, 32, pp. 923-932, 1975.
- McCutcheon, A. L., *Latent Class Analysis*. Sage: Newbury Park, 1987.
- Menzel, H., "A New Coefficient for Scalogram Analysis," *Public Opinion Quarterly*, 17, pp. 268-280, 1953.
- Proctor, C. H., "A Probabilistic Formulation and Statistical Analysis of Guttman Scaling," *Psychometrika*, 35, pp. 73-78, 1970.
- Schwartz, J. E., "A General Reliability Model for Categorical Data Applied to Guttman Scales and Current Status Data," in N. B. Tuma (ed.), *Sociological Methodology*. Jossey-Bass: San Francisco, 1986.
- Sorenson, A. M., and D. Brownfield, "Patterns of Adolescent Drug Use: Inferences from Latent Structure Analysis," *Social Science Research*, 18, pp. 271-290, 1989.
- Stewart, A. L., J. E. Ware, and R. H. Brook, "Advances in the Measurement of Functional Status: Construction of Aggregate Indexes," *Medical Care*, 19, pp. 473-488, 1981.
- Traub, R. E., and Y. R. Lam, "Latent Structure and Item Sampling Models for Testing," *Annual Review of Psychology*, 36, pp. 19-48, 1985.
- Uebersax, J. S., C. S. Poulsen, E. Sobel, and V. Henderson, *The Mixed Markov and Related Stochastic Models for the Analysis of Disease Progression*. RAND: Santa Monica, P-7671, September 1990.
- Walker, L. J., B. deVries, and S. L. Bichard, "The Hierarchical Nature of Stages of Moral Development," *Developmental Psychology*, 20, pp. 960-966, 1984.